MODELING NONLINEAR NEURAL OF TWO LINKS OF A ELECTROMECHANICAL ROBOT OF THREE DEGREES OF FREEDOM

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Abstract. *The objective is the nonlinear neural modeling of two links of a robot manipulator electromechanical of three degrees of freedom (3 DOF). The manipulator comprises three rotary joints and three links, with two links driven by direct current motors, and an third link with motion controlled by a mechanical system that always keeps its the horizontal position. The measurements of angular positions of the joints are made by potentiometers. Manipulator robot models are obtained using equations of Newton-Euler or Lagrange; and are coupled and nonlinear. In this paper, a nonlinear neural model is obtained using the excitations and responses collected of the two links driven by direct current motors and of the an artificial neural network. Finally, we present results obtained from the generated model*

Keywords: *Robotics, Nonlinear neural identification*

1. INTRODUCTION

The manipulators are defined as combinations of rigid structural elements (links) connected to each other through a joint or joints, which at its end is placed a tool or device for performing the task (Lewis, et. al., 2004).

For robotic manipulators project is usually necessary to have a mathematical model for the project then its controlling. These models can be obtained using the physical laws (white box model) or using identification techniques using system input and output (black box models). White box models of these systems are nonlinear (Spong and Vidyasaga, 1989) and difficult to obtain when all the phenomena that occur are considered, while the black box modeling (Aguirre, 2000) can generate linear models and nonlinear.

The systems identification is an area of knowledge that studies alternative techniques of mathematical modeling (Aguirre, 2000; Isermann, 1980; Aström and Wittenmark, 1995; Rubio and Sanchez, 1996; Coelho and Coelho, 2004). One characteristic of these techniques is that little or no prior knowledge of the system is required and therefore such methods are referred as black box modeling (or identification) or empirical modeling (Aguirre et al., 2007).

This work proposes the use of a multilayer neural network (Junior Birth & Yoneyama, 2000) called emulator, to identify the links 1 and 2 of the electromechanical robot manipulator of three degrees of freedom (3 DOF), shown in Fig. 1, using the excitation and angular positions of the two links in question.

2. DESCRIPTION OF THE ROBOTIC MANIPULATOR

The robotic manipulator comprises three rotary joints and three links appointed 1, 2 and 3, as show in Fig. 1. The total displacement of the link 1 is 180º and of the link 2 is 110º, with each of these links being driven by a direct current motor, while the link 3 has its motion controlled by a mechanical system that always keeps the horizontal position.

3. NONLINEAR NEURAL MODELING OF TWO LINKS OF A ROBOT MANIPULATOR

The dynamics of a system may be described in a linear or non-linear fashion. A multilayer neural network (Haykin., 1994; Beale et al, 1991) can be used to learn the input-output mapping defined by the dynamic equations or from data obtained directly from an actual system. Miller III et al. (1995) and Cavalcanti (1994) have proposed various structures of neural controllers, these structures are based on determining the dynamic system, where the multi-layered neural network is called emulator, and in the inverse dynamics of the plant to be controlled, where the neural network is called an inverse neural network. With the emulator obtains system characteristics (plant) through the weights trained, which represent the identified parameters of the system. These weights are used directly for simulation of the system model. The Figure 2 shows a block diagram representing the system and the emulator with the training conducted through backward propagation (BP) algorithm, where U is the input or excitation of the system, Y the output or response of the system, $\hat{Y}$ the a output or response obtained through of the training of the neural network, and E_i the error between the real response and the obtained through the network training.

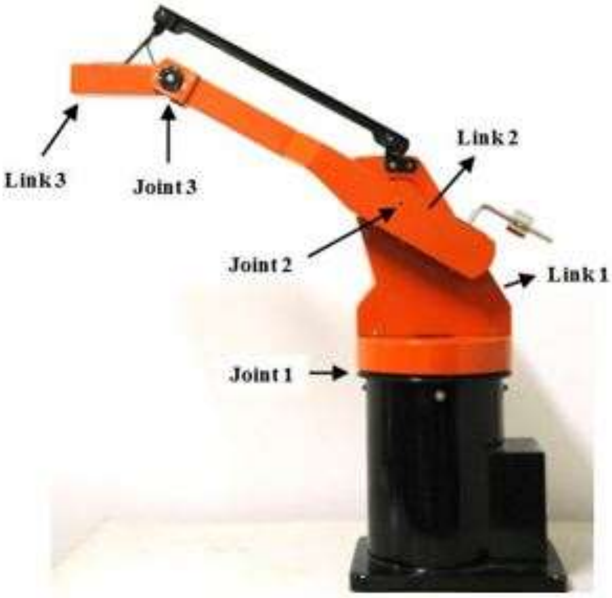

Figure 1. Robotic manipulator comprises three rotary joints and three links

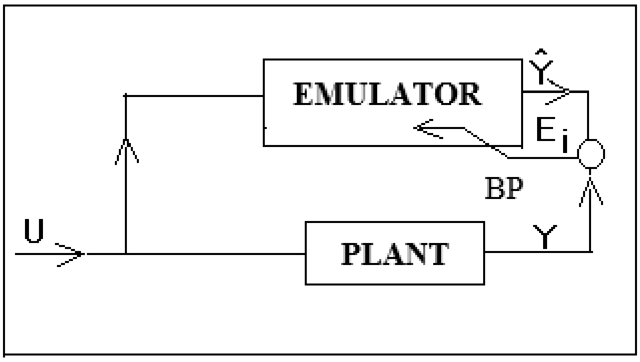

Figure 2. Block diagram with the system and the emulator

The emulator is designed in two stages: the first, the dynamics of the plant is trained, and in the second, the trained weights are used as the identified system model parameters.

The neural network under analysis, shoe in the Fig. 3, has six linear neurons (L) in the input layer (E), twenty nonlinear neurons in the hidden layer (I) activated by hyperbolic tangent function (tgh) and two linear neurons (L) in the output layer (S).

The Equations (1) to (6) are used to calculate the output of each neuron of each layer of the network.

$$y_j^E = x_j^E \tag{1}$$

$$x_k^I = \sum_j w_{jk}^{EI} y_j^E = \sum_j \left(w_{jk}^{EI} y_j^E \right) + T_k^I \tag{2}$$

Substituting Eq. (1) in Eq. (2), are obtain:

$$x_k^I = \sum_j w_{jk}^{EI} y_j^E = \sum_j \left(w_{jk}^{EI} x_j^E \right) + T_k^I \tag{3}$$

$$y_k^I = f\left(x_k^I \right) \tag{4}$$

$$x_m^S = \sum_k w_{km}^{IS} y_k^I \tag{5}$$

$$y_m^S = x_m^S = \sum_k w_{km}^{IS} y_k^I \tag{6}$$

where: x_j^E is the j-th input neuron in input layer E, y_j^E the j-th output neuron in input layer E, x_k^I the k-th input neuron in middle layer I, y_k^I the k-th output neuron in middle layer I, x_k^S the k-th input neuron in output layer S, y_k^S the k-th output neuron in output layer S, w_{jk}^{EI} element of the weight matrix in input layer E, w_{km}^{IS} element of the weight matrix in output layer S, f(.) activation function, T_k^I bias of the k-th neuron in middle layer.

In the first step, which is called training phase performed "offline", the input and output weights of the emulator are trained using input data, which are: $u_1(k)$, $u_1(k-1)$, $\beta_1(k-1)$, $u_2(k)$, $u_2(k-1)$, $\beta_2(k-1)$, the backpropagation (BP) algorithm for obtaining output signals, $\hat{\beta}_1(k)$ e $\hat{\beta}_2(k)$ through minimization of the performance index (I_w) given by Eq. (7).

$$I_w(k) = \frac{E_i^2}{2} = \frac{[Y(k)\text{-}\hat{Y}(k)]^2}{2} \tag{7}$$

where: $u_1(k)$ and $u_2(k)$ are the system inputs, $\beta_1(k)$ and $\beta_2(k)$ the system outputs, Y(k) output vector of the links and $\hat{Y}(k)$ output vector of the emulator.

The adjustments of the network weights are obtained as Eq. (8) and Eq. (9):

$$w_{km}^{IS}(k) = w_{km}^{IS}(k-1) + \mu(\nabla I_w(w_{km}^{IS}))(k-1) \tag{8}$$

$$w_{jk}^{EI}(k) = w_{jk}^{EI}(k-1) + \mu(\nabla I_w(w_{jk}^{EI}))(k-1) \tag{9}$$

where: μ is the training factor emulator and k the number of samples collected.

Once the training phase, the weights and are stored and are used in the second stage for simulation of the robot links model.

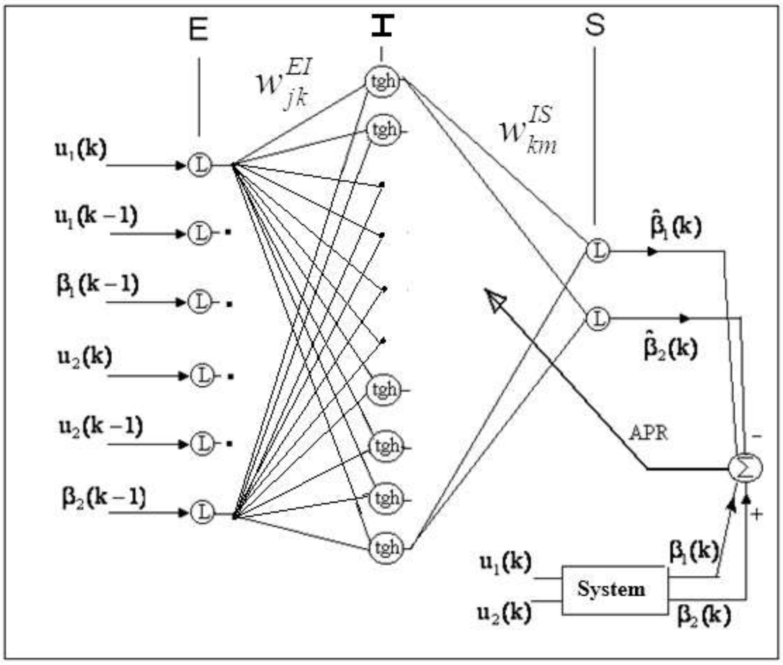

Figure 3. Emulator - Training Phase

4. RESULTS FOR ROBOT LINKS

The Figure. (4) show the input and output signals of the link 1, the Fig. (5) the input and output signals of the link 2., the Fig. (6) the real and trained output of the link 1, the Fig. (7) the real and trained output of the link 2. The trained outputs in the Fig. (5) and Fig. (6) were obtained considering: data 600 samples for each link, neural network of 3 layers, show Fig. (3), trained with: training factor $\mu = 0.9$ and 15 epoch, using the error backpropagation algorithm of Levenberg-Marquardt.

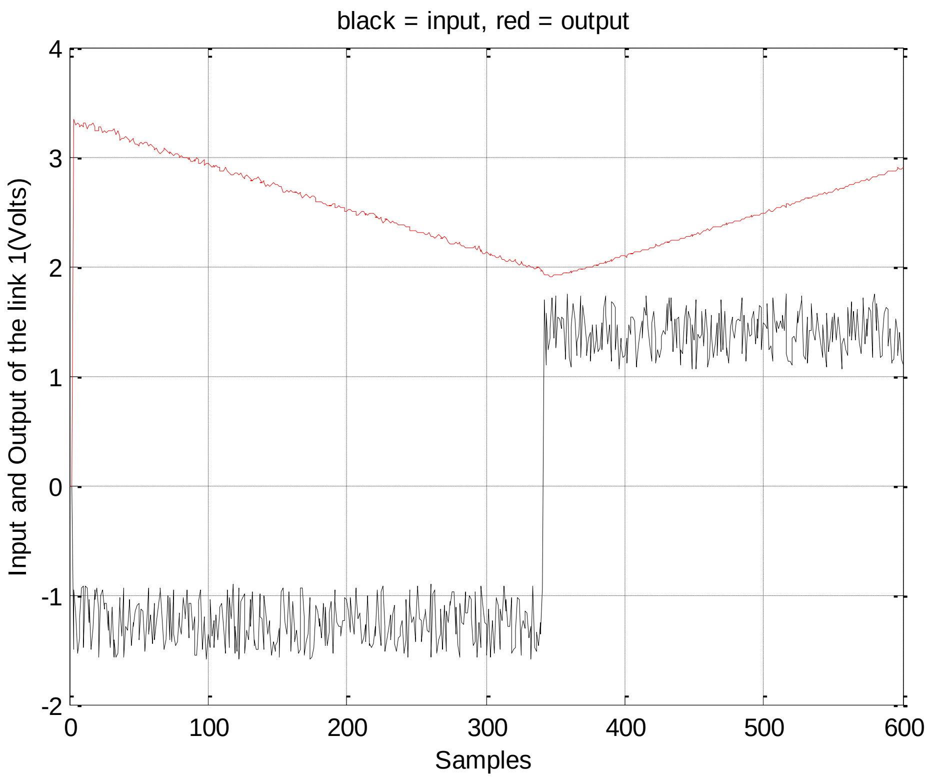

Figure 4. Input and output signals of the link 1

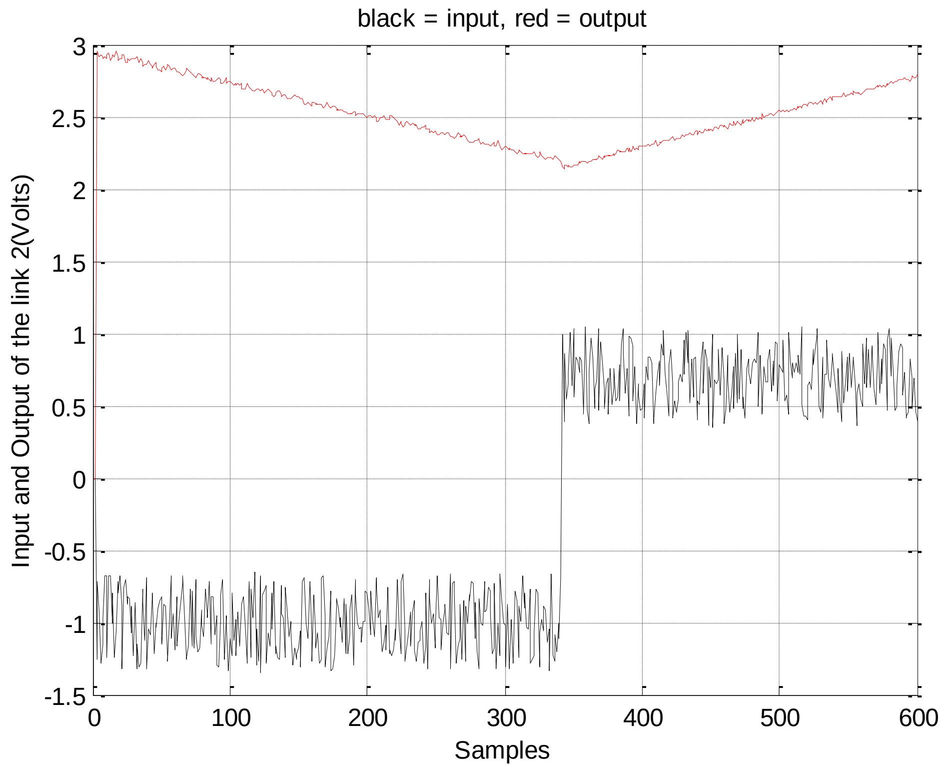

Figure 5. Input and output signals of the link 2

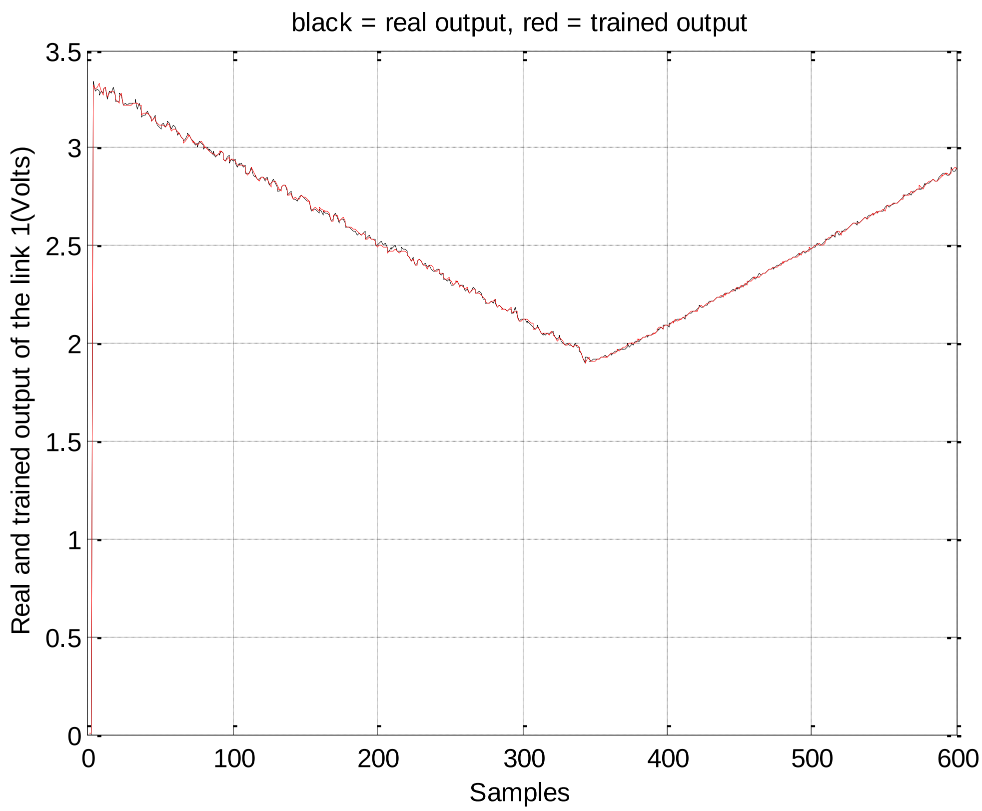

Figure 6. Real and trained output of the link 1

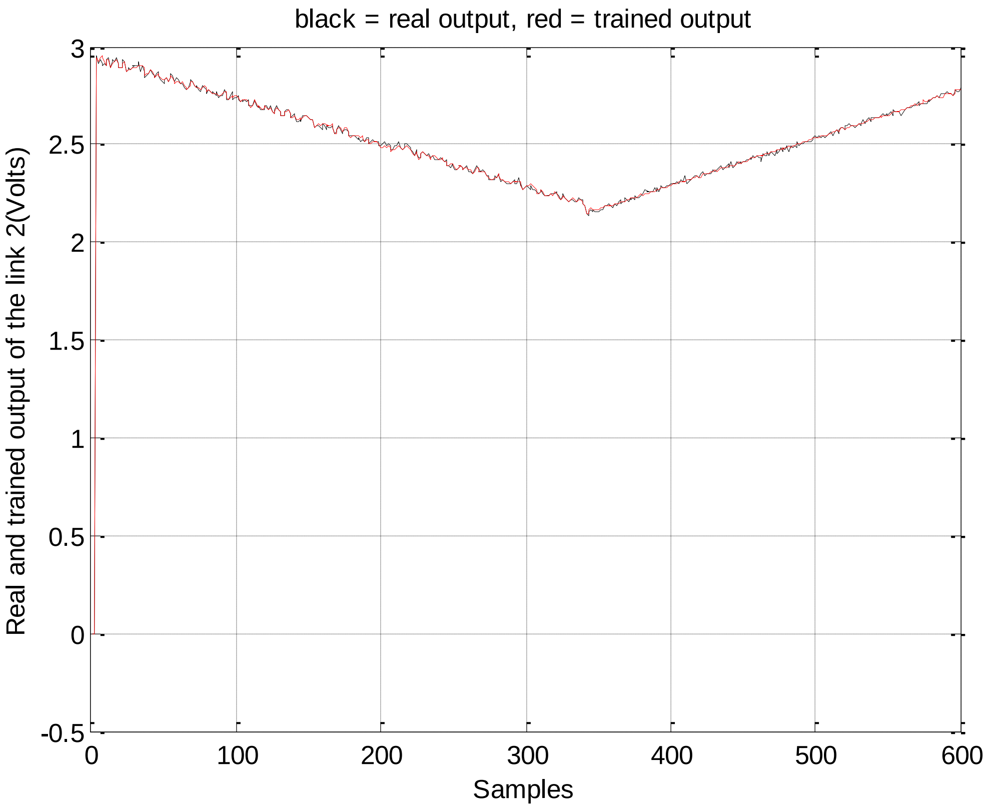

Figure 7. Real and trained output of the link 2

5. CONCLUSIONS

This work showed nonlinear neural technique identification for two links a robot manipulator electromechanical of three degrees of freedom. The identification of links was performed using a neural network, and data from the two links of the robot.

The network was trained and results showed in the Fig. (6) and Fig. (7) indicated that the estimated outputs are representative compared with the real output; which characterizes the system was identified in a satisfactory manner. Therefore the modeling nonlinear neural of two links of the robot proved to be a simple and satisfactory technique where the weights trained by the network can be used in simulations or controlling projects.

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